Unexceptional Exporter Performance in China? The Role of Processing Trade*

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Abstract

The firm level trade literature finds that exporters are exceptional performers for a wide range of countries and measures. Paradoxically, the one documented exception is the world's largest exporter, China. This paper shows that this puzzling finding is entirely driven by firms that engage only in export processing—the activity of assembling tariff-exempted imported inputs into final goods for resale in foreign markets. We find that processing exporters are less productive than non-processing exporters and non-exporters, and have poor performance in many other aspects, such as profitability, wages, R&D, and skill intensity. Accounting for processing exporters explains the abnormality in exporter performance in China that has been documented in the previous literature. Low fixed costs of processing exporting and the trade and industrial policies favoring processing exporters are responsible for the low productivity of processing exporters. Our findings suggest that distinguishing between processing and non-processing exporters is crucial for understanding firm-level exporting behavior in China. The findings also provide caveats in analyzing exporter performance in other developing countries that are highly integrated into global value chains.

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1 Introduction

The nature of international trade has changed. As Grossman and Rossi-Hansberg (2006) put it: It's not wine for cloth anymore. In the modern world, with rapid progress of communication and technology, production processes increasingly involve global value chains (henceforth GVCs) spanning multiple countries, with different stages of the production process taking place in several disparate locations. A particular form of this fragmented production technique is processing trade: the activity of assembling tariff-exempted imported inputs into final goods for resale in foreign markets. The iPhone is a classic example. The various components of an iPhone are manufactured in Germany, Japan, Korea, Taiwan, and the United States from where these are shipped to China for the final assembly at Foxconn, an exclusive iPhone assembler located in Shenzhen. All final assembled products are exported back to the United States and other markets. In terms of its sheer magnitude, processing trade in China merits special attention. Processing trade accounts for nearly half of China's exports, exceeding total exports for most countries except Germany and the United States. Processing/assembly has become popular in other developing countries as well. In 2006, 130 countries had established 3,500 export processing zones (EPZs), which employed 66 million people in total. For many countries (Argentina, Kenya, Malaysia, etc.), exports from EPZs accounted for over 80 percent of their total exports (International Labor Office 2007).

To the best of our knowledge, this paper is one of the first to study the performance of processing firms vis-a-vis non-processing ones. Using comprehensive firm-level data that match balance-sheet information with trade information by detailed trade regime, we demonstrate that processing exporters in China are very different from the traditional exporters in that they do not exhibit the exceptional performance of exporters as documented for a wide range of countries and measures. We also show that accounting for this difference is crucial. In fact, if all exporters are treated the same in China, a puzzling result emerges: contrary to the accumulated evidence in the literature, exporters are no longer superior performers.[1] We show that these puzzling findings are largely driven by firms purely

[1] That exporters in China are less productive than non-exporters has been documented in Lu et al. (2010) and Lu

engaged in processing trade, whereas other types of firms have the usual superior performance.

We first systematically document the performance of processing exporters. Our main findings are as follows. First, processing exporters are less productive than non-processing exporters and non-exporters. Second, processing exporters are special in other aspects as well. These firms have lower profitability, pay lower wages, are relatively smaller in terms of sales, have lower capital intensity, invest less in research and development (R&D), and are less skill intensive. Finally, it is crucial to account for processing exporters separately, since failing to do so makes all exporters appear less productive than non-exporters, although the performance of non-processing exporters is similar to what has been widely documented in the literature. Henceforth, studies of export performance in China (or countries with large processing trade sectors, such as Mexico and Vietnam) should account for the distinction between processing and non-processing sectors.

We next investigate why processing exporters are less productive. We propose a selection mechanism that rationalizes the lower productivity of processing exporters over non-processing ones. Firms trade off the benefits and costs of different trade modes. Compared with non-processing trade, processing trade mainly has two benefits. First, it is associated with lower fixed costs of exporting, because the exporting costs in distribution, marketing, and R&D are shared by the foreign buyer. Second, the trade and industrial policies favoring processing trade, such as exemptions of input tariffs and reductions of corporate income tax rates, further reduce the costs of processing. However, processing trade is also associated with additional costs. Since processing firms generally contribute less than non-processing firms to the value of the final good, processing firms have to share a larger proportion of profits with other producers. Under this framework, firms with different productivity will optimally sort into different trade modes. Less productive firms will select into processing exporting, because the benefits of lower fixed costs outweigh the costs of profit sharing, while for more productive firms, the opposite is true, so they select into non-processing.

Empirically, we find that the low fixed costs of exporting and the trade and industrial policies favoring processing trade are responsible for the low productivity of processing exporters. For the role of the fixed costs of exporting, we find that processing exporters are particularly less productive in

(2010).

industries that are intensive in distribution, advertising, and R&D - elements which are usually thought to be the important components of the fixed costs of exporting. We also find that the productivity of firms engaged in pure assembly (which arguably has lower fixed costs of exporting than processing with imported materials (PWIM), because of its passive role in obtaining materials and searching for clients) is lower than that of firms engaged in PWIM. For the role of trade and industrial policies, we find that input tariff exemptions and income tax benefits matter. First, the relative productivity of processing exporters is lower in the sectors where the benefits of input tariff exemptions are larger. Second, processing firms that are eligible for the income tax benefits granted to export-oriented firms have particularly low productivity. In addition, controlling for eligibility for the tax benefits reduces the productivity disadvantage of processing exporters to a large extent.

The analysis provides a significant caveat in analyzing the performance of exporters in countries that are highly integrated into GVCs. It highlights that the connection between trade, productivity, and other firm outcomes within GVCs is likely to be complex, especially when the integration into the global production network is accompanied by discriminative trade and industrial policies. The analysis also underscores the importance of a firm's place and role within a GVC as a potential determinant of its productivity and other performance measures. We are not aware of any studies that investigate the performance of processing trade firms in countries other than China, so it is yet to be established whether the unexceptional performance of processing firms found in the Chinese data is generalizable to other developing countries as well. For other developing countries interested in increasing GVC participation and learning from China's experience, it will thus be important for future research to examine whether processing trade generally has these kinds of implications.

This paper is related to the firm-level trade literature analyzing the behavior of exporters. Papers like Bernard and Jensen (1995, 1999, 2004), Bernard and Wagner (1997), Clerides et al. (1998), Aw et al. (2000), Pavcnik (2002), Greenaway and Kneller (2004), Blalock and Gertler (2004), Van Biesebroeck (2005), and De Loecker (2007) find that exporters are more productive than non-exporters for a wide range of countries. Two recent papers, however, find the opposite result for China, with exporters being less productive than non-exporters. The paper by Lu et al. (2010) shows that the anomalous result is true only for exporters that are foreign-owned-firms. Another paper, by Lu (2010), finds that exporters are less productive than non-exporters only in labor-intensive sectors. In this paper, we match the firm level data used in the two prior works to the Chinese customs trade data.[2] The use of merged data allows us to identify a firm's processing status and uncover new systematic patterns about how firms' productivity varies with processing status.

This paper is also related to the literature studying GVCs. Although many papers, theoretical and empirical, have studied international vertical specialization and GVCs (Feenstra and Hanson 1996, 1999, 2005; Hummels et al. 1998; Hummels et al. 2001; Yi 2003; Hanson et al. 2005; Grossman and Rossi-Hansberg 2008; Costinot et al. 2013; Johnson and Noguera 2012, etc.), none of these papers has investigated firms along GVCs from a developing country's point of view. The present paper aims to fill this gap.

Lastly, there is an emerging literature documenting the special features and implications of processing trade. At the micro level, recent studies have revealed interesting patterns of processing exporters, including vertical integration (Fernandes and Tang 2012), product scope (Fernandes and Tang 2015), and exporting dynamics (Fernandes and Tang 2015). At the macro level, studies have found that processing trade is associated with aggregate consequences. Bergin et al. (2011) show that industries that are more involved in processing trade are associated with higher volatility. Defever and Riãno (2014) show that subsidies toward processing exporters lead to domestic welfare loss. Finally, processing trade is shown to be important in understanding value-added trade. Koopman et al. (2012) show that using traditional methods for calculating value added for countries that actively engage in processing trade can overestimate the domestic content of these countries' exports. Kee and Tang (2015) study the patterns and determinants of domestic value added of Chinese processing exporters. Our paper is distinct from these studies, as we focus on processing trade and productivity. We show that processing exporters are less productive, and accounting for this special feature of processing exporters has important implications in understanding the link between trade and productivity in general.

The paper is organized as follows. Section 2 briefly introduces China's export processing regime. Section 3 describes the data. Section 4 provides several stylized facts about processing exporters in

[2]The firm-level data do not provide any information about the firms' processing status. This information is available from the customs data; hence, use of the merged data is crucial.

China and relates them to the productivity abnormality documented about Chinese exporters. Section 5 offers possible interpretations about processing exporters' unexceptional performance and how well they are supported by the data, and discusses the dynamics of processing status. The last section concludes.

2 China's Export-Processing Regime

The Chinese government has been actively promoting processing trade since the 1980s to stimulate exports. Processing trade is defined as "business activities in which the operating enterprise imports all or part of the raw or ancillary materials, spare parts, components, and packaging materials, and re-exports finished products after processing or assembling these materials/parts."[3] Compared with non-processing trade (which is also usually referred to as ordinary trade), processing trade involves several notable characteristics. First, processing trade is heavily dependent on importing intermediate inputs. A large proportion of parts and components, especially those that embed sophisticated technologies, are sourced from abroad. In contrast, ordinary trade is often done exclusively with local inputs. Second, in a processing relationship, the Chinese party is mainly in charge of the manufacturing process, and the foreign buyer is usually responsible for the marketing and distribution of the final product to end users. For non-processing trade, however, the Chinese party is also responsible for the design, marketing, and distribution.

Another important aspect of difference between processing and non-processing trade is that processing trade receives special policy treatment from the government. The most distinct difference is input tariffs. For processing exports, imported inputs used in the making of the finished products for export are exempt from any tariffs and import-related taxes. However, all finished products using the duty-free materials have to be re-exported. If such goods have to be sold in the domestic market, approval must be obtained from the commerce authorities in charge of processing trade at the provincial level as well as the Customs authorities. If approved to sell domestically, the processing firm must pay back all the exempted taxes plus interest payments.

[3] The definition is taken from "Measures of the Customs of the People's Republic of China on the Control of Processing-Trade Goods," which was released in 2004 and amended in 2008 and 2010.

Another policy favoring processing exporters is the income tax benefits granted to export-oriented firms.[4] According to China's policies, firms receive a reduced corporate income tax rate if they export the majority (the most common threshold is 70 percent) of their production. Depending on the firm's ownership and location, tax rates granted to export-oriented firms are generally 5 to 15 percent lower than tax rates for firms that are not export-oriented. Although this policy is not specifically targeted toward processing exporters, a large share of processing exporters are export-oriented and thus eligible for such tax benefits. Table A1 in the Appendix demonstrates that processing firms are associated with high export intensity. Processing firms on average export 76 percent of output, while non-processing firms only export 40 percent. Over 70 percent of processing firms have export intensity over 0.7 and 51 percent export their entire production. The corresponding statistics for non-processing firms are, respectively, 32 and 14 percent. Thus, compared with non-processing exporters, a larger share of processing exporters are subject to the tax benefits granted to export-oriented firms.

China has two regulatory regimes for processing exports: pure assembly[5] and PWIM.[6] Pure assembly refers to "business activities in which the operating enterprise receives materials/parts from a foreign enterprise without needing to pay foreign exchange for the import, and carries out processing or assembling with the materials/parts as per the requirements of the foreign enterprise, only charging for the processing or assembling, while any finished products are to be sold and marketed by the foreign enterprise." By contrast, PWIM refers to "business activities in which the operating enterprise imports materials/parts by paying foreign exchange for their processing, and exports finished processed products for sale abroad."

There are some key differences between these two processing regimes. First, for pure assembly, a Chinese firm passively receives orders and materials from its foreign client and exports all the processed goods to this material supplier. By contrast, for PWIM, the firm plays a more active role in obtaining the materials and exporting the processed goods (although not usually the marketing and distribution in foreign markets). The processed goods can also be sold to firms other than the material supplier.

[4] Defever and Riãno (2014) provided a detailed description of this policy (which they refer to as "subsidies with export share requirements") and analyzed its welfare implications.

[5] This is also referred to as "processing with supplied materials."

[6] Pure assembly also refers to "processing with supplied materials" and processing with assembly, as adopted in Yu (2015). Correspondingly, PWIM is also called input and assembly and processing with inputs.

Second, for pure assembly, a Chinese firm obtains raw materials and parts from its foreign trading partners without making any payments. By contrast, for PWIM, the Chinese firm pays for the imported materials. Combining these differences suggests that firms engaged in PWIM are usually faced with higher fixed costs of exporting, either in searching for suppliers and buyers, or in obtaining external finance to cover the costs of exporting. We will exploit these differences across detailed processing regimes in our subsequent analysis.

3 Data

3.1 Firm-Level Production Data

The firm-level data in this paper comes from annual surveys of industrial firms (ASIF) conducted by the National Bureau of Statistics of China from 2000 to 2006. The survey includes all state-owned enterprises and non-state-owned enterprises with annual sales of RMB five million (or equivalently, about $830,000) or more. The data set includes information from balance sheets of profit and loss and cash flow statements of firms, includes about 80 variables, and provides detailed information on firms' identification, ownership, export status, employment, capital stock, and revenue. These firms contribute about 98 percent of total Chinese manufacturing exports in the aggregate trade data. To clean the data, following Feenstra et al. (2014) and Yu (2015), we drop observations that report missing or negative values for any of the following variables: total sales, total revenue, total employment, fixed capital, export value, and intermediate inputs, and if export value exceeds total sales or the share of foreign asset exceeds one. We include firms with at least eight employees. We also restrict the sample to manufacturing firms. However, these data provides no information about a firm's processing status.

3.2 Transaction-Level Trade Data

The transaction-level trade data come from China's General Administration of Customs and spans 2000 to 2006. The data cover the universe of China's exporters and importers, and contain disaggregate product-level information on firms' trading price, quantity, and value at the HS8 digit level.

Importantly, these data provide information on whether a transaction was processing or not, which allows us to construct firms' processing status.

3.3 Matching the Two Data Sets

Matching the firm-level data with the transactions-level data is challenging because the firm identifiers used in the two data sets are different—a nine digit identification number in the firm-level data versus a ten digit identification number in the customs data, with no common elements. To address this problem, we match the firms in the two data sets using firm name, telephone number, and zip code. The details of the merged variables are provided in Appendix A. Finally, we are able to merge about 45 percent of the exporters in the firm-level production data. These firms account for 58 percent of total export value in the firm-level production data, and 25 percent of China's total exports during 2000-2006. Table A1 provides the summary statistics of the merged exporters. In addition to the merged exporters, we also keep all non-exporters in the ASIF data. Taken together, there are 1,244,382 observations from 424,546 firms in our final merged sample. These include 225,853 observations from 68,865 exporters, and 1,018,529 observations from 355,681 non-exporters.

Since the merged sample does not include the universe of exporting firms, a natural concern is sample selection. A good way to examine the representativeness of the data is to check whether the merged data can replicate the counter-Melitz findings documented in the previous literature. Reassuringly, it turns out that the counter-Melitz findings hold very well in the merged data. Exporters in the merged data are less productive in foreign-invested enterprises (FIE) and in labor-intensive sectors, as in Lu et al. (2010) and Lu (2010). This ensures that the firm selection problem in the merged data does not affect the anomalous behavior of exporters found to hold in the original un-merged data.[7]

[7]The results are presented in Table A3 in the Appendix. Column 1 shows that exporters are less productive than non-exporters within foreign-owned firms. Column 3 shows that in terms of value added per worker, exporters are less productive in labor-intensive sectors but are more productive in capital-intensive sectors.

4 Stylized Facts on Processing Exporters

4.1 Ownership and Sectoral Distribution

We start by showing the importance of processing exports in total Chinese exports. We divide all exporting firms into three types depending on the nature of their transactions in a given year: (1) processing firms that only engage in processing transactions (referred to as "processing firms"); (2) non-processing firms that only engage in non-processing transactions (referred to as "non-processing firms"); and (3) firms that engage in processing and non-processing transactions (referred to as "hybrid firms"). Table 1 reports the number of firms and the share of export value for each type of firms. Over the sample period, approximately 14 percent of firms accounting for 17 percent of export value are purely engaged in processing trade. These numbers slightly increase to 15 and 21 percent, respectively, in the merged data. Another 23 percent of firms accounting for nearly 60 percent of export value are engaged in both processing and non-processing.[8]

[Insert Table 1 Here]

Next we show the ownership and sectoral distributions of processing exporters. Motivated by the literature on the unexceptional exporter performance in China, we divide all firms into FIE and non-FIE according to their registration type, and all sectors into labor-intensive, medium, and capital-intensive sectors according to the medium capital-labor ratio in each sector. Table 2 reports the share of exports from three types of exporters as well as the share of processing exports in each subsample. Two facts stand out immediately. First, processing exports are concentrated in multinational firms. 82 percent of exports of FIEs belong to processing trade, and 25 percent of them come from pure processing firms. By contrast, in non-FIEs, these shares are 27 and 5 percent, respectively. Second, processing exports

[8] The main reason why a firm engages in both processing and non-processing trade is that firms may export multiple products, some products through processing and others through non-processing. To see this, Table A4 in the Appendix reports the share of observations with different processing status at different levels of aggregation. We change the level of aggregation from firm-year to firm-product-year (product is defined at the HS 6-digit level), then to firm-product-country-year. At the firm level, 23 percent of firms export through both processing and non-processing. However, at the firm-product level, only 3 percent of firm-product pairs are exported through both trade modes. This suggests that the majority of firm-product pairs is exported through a single trade mode. At the firm-product-country level, the share of observations exported through both trade modes is almost the same as for the firm-product level. Thus, conditional on product, export destination does not seem to explain why firms engage in both activities. It is the product dimension that makes a large difference.

are more concentrated in labor-intensive sectors than in capital-intensive sectors. Processing exports account for 66 percent of total exports in labor-intensive sectors but only 39 percent in capital-intensive sectors. The export share of pure processing exporters is also higher: 21 percent in labor-intensive sectors and 13 percent in capital-intensive sectors.

The facts that processing exports are concentrated in FIEs and in labor-intensive sectors have interesting implications. Previous studies on the performance of exporters in China found that Chinese exporters are less productive than non-exporters in FIEs and labor-intensive sectors. The concentration of processing firms in these ownerships and sectors suggests that the low productivity of exporters in these ownerships and sectors found in the previous literature was possibly driven by the presence of processing exporters. If processing exporters are less productive than non-exporters in these ownerships and sectors, then pooling all exporters (which are skewed to processing exporters) together will lead to the puzzles documented in the literature.

[Insert Table 2 Here]

4.2 Productivity of processing exporters

To examine the productivity of processing exporters versus non-processing exporters and non-exporters, we estimate the following equation:

$$y_{it} = \alpha + \beta_1 PX_{it} + \beta_2 NPX_{it} + \beta_3 BX_{it} + \gamma \mathbf{D}_{it} + v_j + \varsigma_p + \lambda_t + e_{it}, \tag{1}$$

Where y_{it} is the productivity of firm i in year t. PX_{it} is a dummy that equals 1 if a firm is a processing exporter (i.e., in any given year these firms only report processing transactions); NPX_{it} is the dummy for non-processing exporters (i.e., in any given year these firms only report non-processing transactions); BX_{it} is a dummy for exporters engaged in both processing and non-processing trade (i.e., in any year the firms report both processing and non-processing transactions); the omitted group is non-exporters. $\mathbf{D}$ are firm-level control variables. We control for firm size proxied by log total employment, following Bernard and Jensen (1995,1999) and De Loecker (2007). We also include a foreign-invested-enterprise dummy since a firm's processing status is correlated with its foreign-ownership status (see Table 2) and foreign-owned firms usually have higher productivity (Helpman et al., 2004). In addition, we control for a full set of 4-digit industry dummies (v_j), province dummies (ς_p) and year dummies (λ_t).[9]

We calculate total factor productivity (TFP) for each firm-year using the standard techniques in the literature. Our preferred approach is the semi-parametric algorithm developed by Olley-Pakes (henceforth OP, 1996). This approach takes into account the simultaneity of productivity shocks and input choice, as well as the endogenous exit of firms—issues ignored by the traditional ordinary least squares (OLS) TFP measure. We provide a detailed description of our estimation of Olley-Pakes TFP in Appendix B. To ensure our results are not sensitive to the measurement of productivity, we also calculate TFP using the approach proposed by Ackerberg, Caves, and Frazer (henceforth ACF, 2006), which solves the multicollinearity and measurement error issues that the earlier approaches (such as OP and Levinsohn-Petrin (2003)) may suffer; Finally, we also calculate TFP using the traditional OLS approach.

Our baseline regression, Equation 1, allows us to understand the productivity of different types of exporters relative to non-exporters. Table 3 reports our baseline estimation results for the three TFP measures: TFP (OP), TFP (ACF), and TFP (OLS). In columns 1 to 3, we regress TFP against firms' processing status dummies, and control for industry, province, and year fixed effects. We find that the coefficient of the processing dummy is negative and significant, suggesting that processing exporters are less productive than non-exporters. By contrast, non-processing exporters are always more productive than non-exporters, which is consistent with the evidence widely documented by firm-level data in other countries. These results hold consistently for all the TFP measures calculated using different approaches. In columns 4 to 6, we further control for firm size (proxied by log employment) and the foreign ownership dummy. The productivity ranking between processing firms, non-processing firms, and non-exporters is qualitatively unchanged. Quantitatively, in the specification where firm size and foreign ownership are controlled for, processing firms are around 23 to 26 percent less productive than non-exporters, while non-processing exporters are around 11 percent more productive than non-exporters. These results suggest that only the processing exporters demonstrate the counter-Melitz

[9] Industries are based on China Industry Classifications issued by the National Bureau of Statistics. The classification was revised in 2003. We use a concordance to convert the industry classifications in all years into a consistent basis.

productivity pattern.

[Insert Table 3 Here]

We perform a series of robustness checks on the baseline specification. First, it may be a concern that processing and non-processing exporters have different production technologies, which would make their productivity not comparable. To address this, we estimate different production functions for processing and non-processing exporters separately and calculate their measured TFP, respectively.[10] Second, to make sure our baseline results are not driven by omitted variables, we experimented with different sets of fixed effects. Column 2 controls for industry-year fixed effects to account for industry-year specific shocks, while column 3 controls for firm fixed effects to absorb the impact of other time-invariant firm-level characteristics that may correlate with processing status. Third, we weigh each firm by its market share (total sales/industry total sales) in the industry, so that larger firms receive more weight in the regressions. Lastly, we run cross-sectional regressions for each sample year to account for possible structural breaks caused by China's accession to the World Trade Organization (WTO) in 2001, as well as other policy changes that affect processing and non-processing firms differently.[11] The results of these robustness checks are reported in Table 4. Our baseline results hold very well in all these situations. Processing firms are always the least productive among all types of firms, and non-processing exporters are always more productive than non-exporters.

[Insert Table 4 Here]

The above results show that different processing status is associated with different productivity. However, given that firms engage in both processing and non-processing exporting, firms with different productivity may also choose the extent of being engaged in processing exports. Thus, we investigate whether firms' processing intensity (share of processing exports over total exports) is associated with productivity. We regress TFP against processing intensity on the sample of firms that engage in both processing and non-processing. Columns 1 and 2 in Table 5 report the results, column 1 without firm-level controls and column 2 with controls. The results show that firms with higher processing intensity

[10] The estimated production function coefficients are reported in Table A5 in the Appendix.

[11] We only report the results for 2006 because of space limitations. Results for other years are qualitatively similar and are available upon request.

have lower productivity. In column 2, the firm with processing intensity 0.99 (corresponding to the 95th percentile of the processing intensity distribution) is 10 percent less productive than the firm with processing intensity 0.02 (corresponding to the 5th percentile of the processing intensity distribution).

The main reason a firm engages in both processing and non-processing is that it exports different products through different regimes (see footnote 8). Therefore, we also examine whether firms that export a larger number of products through processing are associated with lower productivity. Specifically, we regress TFP against the share of products (HS 6-digit) exported through processing (number of products exported through processing over total number of exported products).[12] The results in columns 3 and 4 in Table 5 suggest that firms that export relatively more product varieties through processing have lower productivity. Taken together, these results suggest that less productive firms are relatively more involved in processing, while more productive firms are more involved in non-processing.

[Insert Table 5 Here]

We next demonstrate whether the low productivity of processing exporters can explain the low productivity of exporters in FIEs and labor-intensive sectors, as found in the previous literature. First, we repeat the regression of Equation 1 on the FIE and non-FIE sample, respectively.[13] Columns 1 and 2 in Table 6 shows that regardless of ownership type, processing exporters are the least productive among all exporters. Moreover, among FIEs, it is only processing exporters that are less productive than non-exporters. Non-processing exporters have the usual superior performance—these firms are more productive than non-exporters. Thus, the finding in Lu et al. (2010) that Chinese exporters are less productive than non-exporters in FIEs is mainly driven by the low productivity of processing exporters. Because processing exports are concentrated in FIEs, pooling all types of exporters will yield the puzzling result that exporters are less productive in general in FIEs.

[12] We define a product to be exported through processing if more than half of its export value belongs to processing. The results are similar if we change the threshold to one-third, two-thirds, or drop products that are exported through both regimes.

[13] We use two methods to identify a firm's ownership type. In the first method, we use the self-reported registration type of the firm, and in the second we calculate the firm's share of stocks owned by foreign partners. Following the definition from the National Bureau of Statistics, we define FIE to be a firm with over 25 percent foreign-owned stocks. The two methods yield qualitatively the same results, so we only report the results using the first method.

Second, we check whether the low productivity of exporters in labor-intensive sectors is also driven by processing exporters. We run the baseline regressions by capital intensity of the sector (low, medium, or high capital intensity).[14] Columns 3 to 5 in Table 6 report the results. Again, it is seen that regardless of the capital intensity of the sector, non-processing exporters are always significantly more productive than non-exporters. It is only the processing exporters that demonstrate the counter-Melitz property. In addition, the productivity disadvantage of processing exporters is most pronounced in labor-intensive sectors, where it is 28 percent compared with 8 percent in capital-intensive sectors. Therefore, the earlier findings that exporters in general are less productive in labor-intensive sectors in China are driven by the fact that processing exporters are particularly less productive in these sectors, and that these sectors have a disproportionately large share of processing exports, as in Table 2.

[Insert Table 6 Here]

4.3 Other Areas of Performance of Processing Exporters

As is evident from the previous analysis, contrary to the widely-documented productivity premium of exporters, the productivity of processing exporters is lower than that of non-exporters. Actually, processing exporters are special not only in productivity, but also in many other attributes for which exporters are found to have superior performance. Table 7 reports the regression results of Equation 1 using various indicators as the dependent variable: capital-labor ratio, total sales, profitability, average wages, R&D expenditure, as well as skill intensity (defined by the share of workers with college education and above).[15] In the literature, exporters are usually found to be larger, more capital intensive, more profitable, pay higher wages, more R&D intensive, and employ relatively more skilled workers compared with non-exporters. In Table 7, we see that this is indeed the case for non-processing exporters, as is suggested by the positive coefficients before the non-processing dummy. In sharp contrast, the performance of processing exporters is strikingly different. Compared with non-exporters, they have lower sales, pay lower wages, are less profitable, invest less intensively in R&D, and employ less skilled workers. These facts further highlight the special nature of processing exporters.

[14] The capital intensity of a sector is constructed at the 2-digit industry level as the median capital-labor ratio in the sector. Similar results are obtained by using the aggregate capital intensity of the sector.

[15] The data for employment by education is only available in 2004, so the regression is run only for that year.

[Insert Table 7 Here]

5 Possible Explanations for the Performance of Processing Exporters

The results in section 4 show that processing exporters are not exceptional performers. In this section, we provide possible explanations for their relatively poor performance. We will mainly focus our discussion on why processing firms have lower productivity, because productivity plays a central role in the heterogeneous-firm trade literature. Lower productivity will naturally lead to smaller firm size, lower wages, lower R&D investments, and lower skill intensity, given certain additional assumptions.

Basically, we believe two factors are mainly responsible for the low productivity of processing exporters. First, processing exports are associated with lower fixed costs of exporting. Second, the trade and industrial policies favoring processing exports, in particular, input tariff exemptions and corporate income tax benefits granted to export-oriented firms, induce low productivity firms to select into processing trade.

5.1 Low Fixed Cost of Processing Exports

The first reason for the low productivity of processing exporters is the low fixed costs of exporting associated with processing. There are several reasons why the fixed cost of exporting might be low. (1) Low distribution cost. In a processing trade relationship, the foreign buyer is responsible for marketing and distribution of the final product. As distribution costs usually account for a large share of total costs (Goldberg and Campa 2010), the cost-saving effect can be large. (2) Low R&D cost. Successful exporting usually requires tailoring the product to consumer tastes or quality upgrading (Verhoogen 2008), which requires substantial investment in R&D. However, in a processing relationship, since the foreign buyer usually provides the know-how and blueprint of the final product, the R&D costs on the processing firm side can be very low. (3) Processing exports usually require fewer up-front costs, which reduces the fixed costs of obtaining external sources of finance. This is especially true for pure assembly, where processing firms receive parts and components for processing without any payment. In sum, the production sharing between the processing exporter and the foreign buyer will help reduce the fixed costs of exporting borne by the processing exporter, making firms that are not productive enough to export through the non-processing regime profitable enough to export through the processing regime.

However, if the lower fixed exporting costs are the only difference between processing and non-processing transactions, all firms will select into the processing regime to take advantage of this lower cost. This cannot explain why in the data some firms choose to export through the non-processing regime, and why firms choosing the non-processing regime are more productive. Therefore, we need another dimension of heterogeneity to rationalize the sorting pattern observed in the data. We argue that this heterogeneity comes from the difference in the variable profit rate between the two trade regimes. Processing transactions are associated with a lower variable profit rate than non-processing transactions. This could arise in an environment of incomplete contracts where the processing exporter and foreign buyer bargain over the distribution of total variable profit, and the share of profits accruing to each party depends on its contributions of value added to the production process. Since processing firms generally contribute less value added than non-processing firms in the production process (Manova and Yu 2013), processing firms receive a smaller share of profit and this transmits into a lower variable profit rate.[16]

When processing and non-processing transactions differ in terms of both fixed exporting costs and variable profit rate, firms will face a trade-off in their selection of exporting mode. Specifically, for firms with a given productivity, non-processing exports yield a higher variable profit rate, but also requires more fixed exporting costs. Firms will choose non-processing over processing if the gains of additional variable profits outweigh the costs of extra fixed payment. Since more productive firms have larger sales, their total variable profits will increase more than that of the less productive firms for a given increase in profit rate. As a result, in equilibrium, firms with higher productivity will optimally select into the non-processing regime, whereas firms with lower productivity select into the processing regime—a pattern consistent with our empirical findings. In Appendix C, we provide a sketch of an augmented Melitz (2003) model that endogenizes the choice of processing versus non-processing exports. Under the assumptions that (1) the fixed costs of processing exports are lower than those of non-processing exports, and (2) the slope of the profit function with respect to productivity is less steep

[16] Although we do not have data on the variable profits of firms, column 4 in Table 7 does show that profitability (profit per worker) is lower for processing firms.

for processing exports, implying that processing activities are associated with lower variable profit, the model shows that less productive firms will self-select into processing exports, while more productive firms self-select into non-processing exports.

In general, it is difficult to test the validity of such selection mechanism directly, since doing so would require data on the fixed exporting costs of processing and non-processing transactions, which to our knowledge is not available. However, in the following we attempt to give some indirect evidence suggesting that the selection story we proposed explains the observed data patterns. First, we try to exploit the variation across industries in their fixed costs of exporting. Our underlying assumption is that the relative fixed costs of non-processing exports are higher in industries with higher fixed costs of exporting. Thus, the productivity of pure processing firms relative to the non-processing ones should be lower in the industries where the fixed costs of exporting are high. To proxy for the fixed costs of exporting across sectors, we use three industry-level indicators constructed by averaging across all exporters within an industry: (1) sales intensity (sales cost over total sales), (2) advertisement intensity (advertisement expenditure over total sales), and (3) R&D intensity (R&D expenditure over total sales), The first two indicators capture the fixed costs of exporting associated with product distribution and marketing. The third indicator captures the fixed costs of exporting associated with design, quality upgrading, or product or process innovation. We further divide all industries into two groups by using the median of each indicator as the cutoff. To compare the productivity between processing and non-processing exporters, we regress TFP on a dummy indicating processing exporting and a dummy indicating both processing and non-processing. The omitted group is non-processing exporters. We run regressions for each industry group.

[Insert Table 8 Here]

The results are reported in Table 8. In all the industry groups, processing exporters are less productive than non-processing exporters. However, in industries where the fixed costs of exporting are high, processing exporters' productivity disadvantage is more pronounced. This holds true regardless of the indicator used to proxy for the fixed costs of exporting. Therefore, the data support our theoretical model, which highlights the lower fixed costs of processing exports as the main determinant of processing exporters' lower productivity. In addition, the TFP disadvantage of processing exporters is around 8 percent larger in industries with high sales and advertisement, and 6 percent larger in R&D-intensive industries. These findings suggest that the lower fixed costs of exporting for processing exports come from lower distribution and marketing costs, as well as lower R&D costs, although the distribution cost channel seems to play a more important role.

Further evidence on the fixed cost story can be obtained by exploiting sources of variation that come from the different natures of transactions across China's detailed processing trade regimes. As described in the introduction, compared with pure assembly, PWIM requires the processing firm to play a more active role in sourcing inputs, searching for clients, and exporting the final goods. In addition, PWIM requires up-front payment for the imported components and materials, which brings greater need for liquidity, which might be financed through external sources. Obtaining such external finance is associated with considerable fixed costs in China, where financial frictions are severe (Allen et al. 2005; Boyreau-Debray and Wei 2005). Thus, the theory would predict that the productivity disadvantage of pure assembly exporters should be larger than that of PWIM exporters. To test this, we regress TFP (various measures) on a pure assembly dummy (which equals 1 when firms are engaged only in pure assembly), a PWIM dummy (which equals 1 when firms are engaged only in PWIM), and a dummy indicating hybrid trade regimes. The omitted group is again non-processing exporters. The results in Table 9 indicate that pure assembly exporters are indeed the least productive, being around 43 percent less productive than non-processing exporters. The productivity disadvantage of PWIM exporters is around 30 percent. Therefore, the productivity ranking of firms in different processing trade regimes also supports the fixed cost argument.

[Insert Table 9 Here]

5.2 Tax and Tariff Policies Favoring Processing Exports

As described in section 2, processing exports are subject to various forms of policy benefits. First, the imported inputs that are used to produce outputs for re-export are completely duty-free. Second, conditional on exporting a dominant proportion of output, processing exporters can also enjoy favorable treatment in corporate income tax. These policy incentives encourage more firms to participate in processing exports and lower the productivity threshold of processing exporters. In the theoretical model in Appendix C, we show that a reduction in the variable trade cost of processing exports relative to non-processing exports, which can be interpreted as policies favoring processing exporters such as exemption of input tariffs or reduction of corporate income tax, increases the productivity gap between processing and non-processing exporters. We now empirically investigate the role of input tariff exemptions and the income tax benefits granted to export-oriented firms.

5.2.1 Input Tariff Exemptions

Our empirical strategy of examining the role of input tariffs is to exploit the variation in input tariff levels across industries. Specifically, we investigate whether the productivity gap between processing exporters and non-exporters is higher in industries with a higher level of input tariffs. Since processing exports are duty-free, a high input tariff level makes the tariff exemptions granted to processing exporters more attractive, thus increasing the benefits of processing exports and enabling less productive firms to be engaged in processing. At the same time, a high input tariff level raises the productivity threshold of non-processing exports, because only very productive firms will find it optimal to afford the input tariff costs by exporting through the non-processing regime. Thus, the theory suggests that the productivity gap between processing and non-processing firms should be larger if input tariffs are higher.

To examine this prediction empirically, we construct input tariffs for each 4-digit industry, drawing on product-level tariff data and China's 2002 input-output table.[17] We then divide all sectors into "low input tariff industries" and "high input tariff industries."[18] To compare the productivity of processing and non-processing exporters, we regress TFP against a processing exporter dummy and a "both" dummy, with the omitted group being non-processing exporters. The results are reported in columns 1 and 2 in Table 10. According to the theory, processing exporters should be particularly less

[17] We calculate the input tariff for each industry in the input-output table (henceforth IO industry) as the weighted average of the output tariffs of its upstream industries, with weights reflecting the input structure of the industry. The output tariff of each IO industry is calculated as the simple average of the tariffs of the corresponding HS 6-digit products. We use a concordance to map HS 6-digit products to IO industries. After obtaining the input tariff data at the IO industry level, we map IO industries to 4-digit CIC using the concordance from the National Bureau of Statistics. The industry classification in China's 2002 input-output table is more aggregated than the 4-digit CIC, so the input tariffs are approximately at the 3-digit CIC level. The results are highly consistent with Brandt et al. (2012).

[18] The annual average of tariff rates for the low and high tariff industries are 7.4 and 12.9 percent, respectively.

productive (compared with non-processing exporters) in industries with high input tariffs. The results are supportive of the theoretical predictions. In low input tariff industries, pure processing exporters are 24 percent less productive than non-processing exporters, while in high input tariffs industries, the productivity gap is 30 percent. As an alternative specification, we add to the regression an interaction term between log input tariffs and the processing exporter dummy, as well as an interaction term between log input tariffs and the "both" dummy. The results are reported in column 5. A negative significant coefficient is obtained for the processing$\times$log(tariffs) interaction term. This finding confirms that in sectors with higher tariffs, the productivity of pure processing exporters is even less than that of non-processing exporters. To see how large the differences are across industries, note that log input tariff rates for the lowest tariff sector (corresponding to the 5th percentile of the input tariff distribution) and the highest tariff sector (corresponding to the 95th percentile of the input tariff distribution) are, respectively, 1.56 and 2.89, so the regression results suggest that in the industry with the highest input tariffs, the productivity disadvantage of pure processing exporters is 13 percent $(0.096\times(2.89-1.56))$ larger than in the industry with the lowest input tariffs.

As an alternative check, we also examined whether the negative relationship between firms' processing intensity and productivity (as found in Table 5) is more pronounced in industries with higher input tariffs. Similar to our previous exercise, we run the regression of productivity against firms' processing intensity separately for low input tariff sectors and high input tariff sectors. The results are reported in columns 3 and 4 in Table 10. It is seen that productivity declines with processing intensity at a faster rate in high input tariff sectors. Raising processing intensity from 0 to 1 is associated with 10 percent productivity reduction in the low input tariff sectors; there is a 20 percent productivity reduction in the high input tariff sectors.

In sum, all the above results indicate that in industries in which the benefit of input tariff exemptions is larger (i.e., industries with higher input tariffs), the negative relationship between productivity and processing exports is more pronounced. This implies that the input tariff exemptions offered to processing exporters is indeed an important source of the unexceptional productivity of processing exporters in China.

[Insert Table 10 Here]

5.2.2 Tax Benefits Granted to Export-oriented Firms

Another form of favorable policy treatment granted to processing exporters is the reduction of corporate income tax. As described in the introduction, these tax reductions are not granted specifically to processing exporters, but to firms exporting a large proportion of their output (export-oriented firms). However, since processing exporters usually have high export intensity, they are relatively widely affected by these tax benefits.

To examine how much the tax benefits granted to export-oriented firms explain the low productivity of processing firms, first, we check whether firms that are eligible for the tax benefits have lower productivity. Since most regulations in China take export intensity of 0.7 as the threshold of being an export-oriented firm, we regress TFP against a dummy variable that takes the value of 1 if the firm's export intensity is greater than 0.7. Column 1 in Table 11 shows that being eligible for tax benefits does matter for productivity. Exporters that are eligible are 11 percent less productive than exporters that are not eligible.[19]

Next, we investigate to what extent being eligible for tax benefits can explain the low productivity of processing firms. To show this, we repeat our baseline regression of TFP against processing status, as in Equation 1, but now include the eligible dummy as an additional regressor. The idea is to see, conditional on being eligible for tax benefits or not, whether firms' processing status is still associated with productivity differences. If the low productivity of processing exporters is partially explained by being eligible for tax benefits, controlling for the eligible dummy will reduce the magnitude of processing firms' productivity disadvantage. We see in column 2 in Table 11 that this is indeed the case. After controlling for whether the firm is eligible for tax benefits, processing exporters are only 15 percent less productive than non-exporters, compared with the 26 percent difference in the baseline results in Table 4. It should be noted, however, that even after controlling for the eligible dummy, processing exporters are still less productive than non-processing exporters and non-exporters. This suggests that there are other forces, in addition to tax benefits, that explain the low productivity of

[19] We also tried other thresholds, such as 0.9 and 1. The results are qualitatively similar: firms above the threshold have lower productivity.

processing exporters.

To see this point more clearly, in column 3 in Table 11, we divide firms into subgroups by their processing status and eligibility for tax benefits, and regress TFP against the group dummies (the omitted group is non-exporters). This approach allows us to compare, for example, firms with the same processing status but different tax benefit eligibility. We can also compare firms with the same tax eligibility but different processing status. By doing this, we can separate the role of tax benefits from other factors that affect the productivity of processing firms. Several messages emerge from the results in column 3. First, for a given processing status, eligibility for tax benefits still matters. For example, among pure processing exporters, the eligible firms are about 30 percent less productive than the non-eligible firms. Among non-processing exporters, eligible firms are about 10 percent less productive. Second, given the same eligibility, the productivity of processing and non-processing firms is still systematically different. For instance, among the non-eligible firms, processing exporters are 19 percent less productive than non-processing exporters, and 6 percent less productive than non-exporters. Among eligible firms, processing exporters are 40 percent less productive than non-processing exporters.

Taking these results together, we conclude that the favorable tax policy toward export-oriented firms is indeed a driving force behind the low productivity of processing exporters. However, the productivity disadvantage of processing exporters is still present when the analysis controls for eligibility for tax benefits. Thus, other factors (such as different fixed costs) also play important roles.

[Insert Table 11 Here]

5.3 Alternative Explanations

5.3.1 TFP Measurement Issues

It is possible that TFP measurement issues may make processing exporters appear less productive. Since we use revenue-based TFP to measure productivity (i.e. we use value, instead of quantity, of output and intermediate inputs in the production function estimation), the measured productivity will be biased downward for firms with lower output prices or higher input prices. Processing exporters may appear less productive if they export at a lower price or import intermediate inputs at a higher price. To check this, we directly compare the export and import price of processing and non-processing transactions using the following regressions:

$$\log UV_{ipcht} = \alpha + \beta_1 PX_{ipcht} + \gamma FIE_{it} + v_{pct} + \varepsilon_{ipcht}, \tag{2}$$

Where UV_{ipcht} is the export or import unit-value of product (HS 6-digit) p by firm i to (or from) country c through processing status h. PX_{ipcht} is a dummy variable that equals 1 for processing transactions. The omitted group is non-processing transactions. We control for product-country-year fixed effects (v_{pct}) to absorb any product-country-year specific shocks that may affect export or import price. Thus, the coefficient β_1 in Equation (2) reflects the price differences between processing and non-processing transactions within a product-country category and in the same year. In addition, Ge et al. (2015) find that multinationals charge higher export price in China. Considering the high correlation between processing status and foreign ownership, we include an foreign-invested-enterprise dummy (FIE_{it}) in all the regressions.

We run the price regression on the full customs data and the merged data. The results are reported in Table 12. Column 1 reports the results for export prices using the customs data. It is seen that the export prices of processing transactions are around 3 percent lower than those of non-processing exports.[20] Considering that the majority of output for processing firms is exported, this suggests that output prices for processing exporters are likely to be lower, translating into lower value of output and revenue-based TFP. However, we also need to look at prices on the input side. Higher input prices would lead to downward bias in revenue-based TFP. Column 2 reports the results for import prices.[21] The results, on the contrary, indicate that import prices of processing exports are 86 percent lower than those of non-processing exports. Therefore, price differences on the input side will translate into lower input use and thus higher revenue-based TFP for processing exporters. Taking export and import prices together, it is not clear how the price differences between processing and non-processing exports will bias the measured TFP of processing firms upward or downward. The results using the merged

[20] As in Ge et al. (2015), we also find that multinationals charge higher export prices.

[21] Since all firms in our merged data are manufactures, their imports are likely to be intermediate inputs rather than final goods. We also tried running the regression on the imports of "intermediate inputs" according to the BEC classification, and the results are similar.

data in columns 3 and 4 reveal the same message.

[Insert Table 12 Here]

Admittedly, an exact evaluation of the bias caused by price differences is difficult unless we have very detailed data on all the firms' outputs and inputs (including domestic and foreign). However, there are several reasons we believe that our baseline results reflect the true productivity differences between processing and non-processing firms, rather than being driven by measurement errors. First, we have found that processing exporters are inferior in a wide range of performance indicators, such as wages, R&D expenditures, and skill intensity. These indicators are less susceptible to measurement errors than TFP. The firm heterogeneity literature has established that more productive firms pay higher wages (Amiti and Davis 2011), invest more in R&D (Bustos 2011), and are more skill intensive (Burstein and Vogel 2012), thus processing exporters' poor performance in these aspects is consistent with their low productivity. Second, we have found that the lower productivity of processing exporters is also correlated with input tariffs or tax benefits granted to export-oriented firms in a systematic way. Productivity differences that are entirely driven by measurement errors are not likely to demonstrate such systematic heterogeneity. Third, we have found that processing exporters charge lower price for exports and pay lower price for imported inputs. These findings are consistent with the theory that processing exporters are less productive, and thus import lower-quality inputs to produce lower-quality outputs (Kugler and Verhoogen 2012).

Another related issue is transfer pricing. Subsidiaries of multinationals may repatriate profits to their related parties in other countries by exporting output at an artificially low price, or importing inputs at an artificially high price. Both activities will translate into low revenue-based TFP. However, we believe transfer pricing does not play a key role in explaining the low productivity of processing exporters. First, the corporate tax rate in most of China's major foreign direct investment source countries is higher than in China. According to Ge et al. (2015), among the top 10 countries investing in China (which in total account for about 90 percent of foreign firms), the corporate tax rates range from 24.5 percent (Singapore) to 38 percent (Canada). China's statutory corporate tax rate is 30 percent. However, FIEs receive a great deal of tax holidays and exemptions. Corporate tax for FIEs is completely waived during the first two profitable years and reduced by half in the subsequent three years. In the ASIF data, we find the average of the effective corporate tax rate for FIEs is only 7.5 percent. Thus, a profit-maximizing transfer pricing strategy would require foreign subsidiaries in China to export at a high price and import at a low price, both of which translate into higher revenue-based TFP. If the low productivity of processing firms is purely driven by transfer pricing issues, we would expect the productivity disadvantage of processing exporters to be smaller in FIEs (assuming that transfer pricing is more likely in FIEs and in processing exporters). However, Table 6 finds just the opposite. Second, the literature finds no evidence that transfer pricing issues drive the export price premium of multinationals in China (Ge et al. 2015). One possible reason is that transfer pricing of intangibles (e.g., royalty payments) rather than physical output could be a more effective way for multinationals to repatriate profits.

5.3.2 Other Policies

This section discusses the impact of other policies that may explain the poor productivity of processing exporters.

Export license. The first policy we consider is the export license system. Back in 1990s, the Chinese government restricted the right of firms to engage in foreign trade. Although the number of firms that were granted trading rights increased substantially throughout the 1990s and early 2000s, the designated trading system was not abolished until 2004. After 2004, except for a narrow set of product categories, all firms active in China were given the right to export (Branstetter and Lardy 2008). When the export license system was present, it was possible that the government chose to grant more trading rights to processing exporters but restricted the trading rights of non-processing exports to a narrower set of productive firms. This may also help explain the low productivity of processing exporters.

To examine the role of the export license system, we carry out two exercises. First, since the major reform regarding the export license system occurred in 2004, we examine the productivity of processing exporters before and after the abolishing of the export license system. Column 1 in Table 13 reports the results before the reform and column 2 reports the results after the reform. We see that the productivity of processing exporters relative to non-processing exporters and non-exporters barely changed before and after the abolishing of the export license system.

Second, the Chinese government has set a subgroup of product categories with tight control of the export license (even after 2004). Thus, we examine whether the low productivity of processing exporters still exists in the industries under the restrictions of the export license system, and in the industries that are not restricted. Column 3 reports the results for restricted industries and column 4 reports the results for unrestricted industries.[22] According to the results, the productivity gap between processing and non-processing exporters is almost identical in restricted and unrestricted industries (around 35 percent). Compared with non-exporters, the productivity disadvantage of processing exporters is smaller in restricted industries (18 percent in restricted industries and 26 percent in unrestricted industries). Thus, we do not find evidence that the export license system contributed to the low productivity of processing exporters.

Exchange rate reform. Exchange rate changes may affect the cost of imported intermediate inputs, which are shown to be important determinants of productivity (Amiti and Konings 2007; Halpern et al. 2015). Changes in the exchange rate of the RMB may explain the low productivity of processing exporters if, say, processing exporters benefit less from cheaper imported inputs because of the appreciation of the RMB. To examine this, we first divide all the sample years into two sub-periods: 2000-2005, during which the RMB was effectively depreciating against other currencies, and 2006, during which the RMB began to effectively appreciate. The results in columns 5 and 6 in Table 13 show that in the two sub-periods, the productivity disadvantage of processing exporters is only slightly different, and is smaller for the appreciation period. This is not consistent with the conjecture that processing firms may benefit less from appreciation of the RMB.

5.4 Further Discussion: Dynamics of Processing Status

Our focus in the previous sections was mainly on the static comparison of processing and non-processing firms. We find that less productive firms select into processing while more productive firms select into

[22] Export license data for 2000-2006 were collected from the annual circulars of the Ministry of Commerce. Since the original list is at HS 8-digit or 10-digit level, we used a concordance to map it to 4-digit CIC industries. In 2006, there were 31 (of 422) industries that were restricted.

non-processing. However, another important issue is the dynamics of processing trade. Does a firm's processing status evolve over time as firm productivity grows? Do firms start with processing exports and gradually switch into non-processing exports? Admittedly, a detailed analysis on these dynamic issues is beyond the scope of this paper. However, in this sub-section we provide some preliminary evidence.

Our strategy is to look at the transition matrix of processing status over time. Specifically, given the firm's processing status (non-processing, processing, both) in a certain year t, we calculate the probability of each processing status in year $t+k$. Table 14a reports the matrix for $k=1$ (which we call "short run") while Table 14b reports the matrix for $k=6$ (which we call "long run").

Several patterns emerge. First, firms' processing status is quite persistent over time, at least in the short run. This can be seen by the large numbers on the diagonal of the matrix. Over one year, more than 80 percent of processing exporters still do processing only. For non-processing exporters, the share is even larger (94 percent). Over six years, over 60 percent of processing exporters are still doing processing trade only, and 85 percent non-processing exporters are still fully engaged in non-processing trade.

Second, it is more common for firms to start with processing and then switch into (at least some) non-processing trade, rather than the reverse. Over one year, 17 percent of pure processing exporters will start to do some non-processing trade, and 1 percent will turn into pure non-processing firms. By contrast, only 6 percent of non-processing exporters will start to do some processing, and essentially no firms will transit from pure non-processing exporters to pure processing exporters. For firms that start with both activities, 12 percent will turn into pure non-processing firms, while only 6 percent will become pure processing exporters. Over six years, the evolution into non-processing trade becomes even more evident: 36 percent of pure processing exporters will start to do at least some non-processing trade, and 7 percent will become pure non-processing exporters. By contrast, only 15 percent of pure non-processing exporters will start do some processing, and no firms will become pure processing exporters. For firms starting with both activities, 30 percent will become pure non-processing exporters, while only 7 percent will become pure processing exporters.

In sum, these results suggest that although firms' processing status evolves slowly, there is indeed evidence that firms start with processing trade and then gradually switch to non-processing trade. This is also consistent with our story that processing trade is an "easier" activity (in the sense that it is associated with lower fixed costs, or more favorable policy treatments), so it makes sense for firms to start with processing and switch to non-processing as their productivity grows.

6 Concluding Remarks

Processing trade, in which parts are sourced globally and assembled at one place to be shipped to the final destination, explains bulk of the trade for the exporting powerhouse—China. This paper merged Chinese firm-level balance sheet data with customs trade data to provide new stylized facts about the performance of processing exporters. We showed that processing exporters are fundamentally different from non-processing exporters—the former being not only less productive than the latter, but also less productive than non-exporters. The firm-level trade literature usually finds exporters to be exceptional performers. However, some recent papers on China document that exporters are less productive than non-exporters, both among foreign affiliates and in labor-intensive sectors. We showed that these anomalies are driven by the existence of processing exporters that are the least productive among all types of firms. Our results imply that it is essential to consider processing trade separately from ordinary exporting activity when analyzing exporter performance in countries that have large processing trade sectors.

We explored possible reasons for the low productivity of processing exporters. We proposed a selection mechanism where firms with different productivity select into different trade regimes. Compared with non-processing trade, processing trade is associated with lower fixed costs of exporting because of international production fragmentation. And processing trade is subject to favorable trade and industrial policies, such as input tariff exemptions and income tax benefits. We found supportive evidence that both factors are responsible for the low productivity of processing exporters in China.

Our findings have important policy implications. On the one hand, the re-allocation predictions in the presence of processing exporters are opposite those in the Melitz (2003) model, in which a move toward exporting increases the aggregate productivity of the sector, since exporters are more productive than non-exporters. An export surge driven by processing trade, contrary to this belief, would not imply higher aggregate productivity, since processing firms are the less productive ones. On the other hand, there could be knowledge spillovers or learning by doing from processing, so less productive firms could benefit dynamically from their participation in the global production network. It thus becomes imperative to look into the costs and benefits of export processing. Exporting is often encouraged by countries on the grounds that exporters are more productive and grow faster, so that they can act as an engine of growth. Given our findings, it also makes sense to conduct a more detailed evaluation of learning from processing. This will have important implications for countries conducting processing trade or planning to do so. We plan to study this in the future.

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Table 1: Share of Firms and Export Value, by Processing Status *(percent)*

	Full Customs Data		Merged Data	
	# of firms	Export value	# of firms	Export value
Non-processing	63.0	24.9	52.4	15.0
Processing	14.1	16.9	15.3	21.3
Hybrid	22.9	58.2	32.2	63.7

Note: Non-processing refers to exporters engaging in non-processing trade only. Processing refers to exporters engaging in processing trade only. Hybrid refers to exporters engaging in both processing and non-processing trade.

Table 2: Share of Exports from Different Exporters, by Ownership and Sectoral Capital Intensity
(percent)

Classifications	Ownership		Sectoral Capital Intensity		
	(1)	(2)	(3)	(4)	(5)
	FIE	Non-FIE	Labor int.	Medium	Capital int.
Non-processing	8.5	48.8	17.3	9.7	39.9
Processing	24.6	4.5	21.4	22.8	12.6
Hybrid	66.9	46.7	61.3	67.5	47.5
Share of Processing Exports	81.9	27.1	66.4	81.8	39.2

Note: This table reports the share of exports from non-processing exporters, processing exporters and exporters engaged in both activities. Columns (1) and (2) report the share within foreign invested enterprises (FIE) and non-FIE. Columns (3)-(5) report the share within labor intensive, medium and capital intensive sectors. Labor intensive, medium, and capital intensive sectors are defined based on the 33% and 67% quantile of sectoral capital labor ratio. The last row reports the share of processing exports over total exports in each ownership and sector group.

Table 3: Benchmark Estimates

	(1)	(2)	(3)	(4)	(5)	(6)
Dep. Var.	TFP(OP)	TFP(ACF)	TFP(OLS)	TFP(OP)	TFP(ACF)	TFP(OLS)
Non-processing	0.230***	0.069***	0.185***	0.109***	0.119***	0.113***
	(0.005)	(0.005)	(0.005)	(0.005)	(0.006)	(0.005)
Processing	-0.060***	-0.299***	-0.134***	-0.262***	-0.236***	-0.265***
	(0.010)	(0.011)	(0.010)	(0.011)	(0.012)	(0.010)
Hybrid	0.280***	0.004	0.207***	0.075***	0.080***	0.080***
	(0.007)	(0.007)	(0.007)	(0.007)	(0.008)	(0.007)
Size and FIE dummy	No	No	No	Yes	Yes	Yes
Observations	801,829	801,829	801,829	801,829	801,829	801,829
R-squared	0.302	0.401	0.336	0.314	0.405	0.339

Note: This table reports the regression results of Equation 1. OP: Olley-Pakes, ACF: Ackerberg, Caves, Frazer. The omitted group is non-exporters. All regressions include 4-digit Chinese industry, province, and year dummies. Columns (4)-(6) further include log employment and the foreign-invested-enterprise dummy. Standard errors are clustered at the firm level. * $p < 0.1$, ** $p < 0.05$, *** $p < 0.01$.

Table 4: Additional Robustness Checks for Processing Exporters

Dep. Var.: TFP(OP)	(1) Different technology for proc./non-proc. exporters	(2) Industry-year FE	(3) Firm FE	(4) Weighted regression	(5) Cross-section regression
Non-processing	0.124***	0.111***	0.155***	0.156***	0.112***
	(0.005)	(0.005)	(0.006)	(0.019)	(0.007)
Processing	-0.283***	-0.266***	-0.393***	-0.187***	-0.231***
	(0.010)	(0.010)	(0.012)	(0.039)	(0.016)
Hybrid	0.063***	0.072***	0.023***	0.097***	0.085***
	(0.007)	(0.007)	(0.009)	(0.025)	(0.010)
Time Coverage		2000-2006			2006
Observations	801,829	801,829	801,829	801,525	162,858
R-squared	0.252	0.338	0.012	0.422	0.326

Note: This table reports the results of regression of Equation 1. The dependent variable is TFP (Olley-Pakes). TFP in column (1) is estimated separately for processing and non-processing firms, thus allowing the two types of firms to have different production technology. Column (2) includes industry-year fixed effects plus province fixed effects. Column (3) includes firm fixed effects. Column (4) runs weighted regression using market share as weights. Column (5) reports results for 2006. All columns except (3) include firm-level log employment and the FIE dummy. Columns (1), (4), and (5) include 4-digit CIC industry, province, and year dummies. Standard errors are clustered at the firm level. * $p < 0.1$, ** $p < 0.05$, ***$p < 0.01$.

Table 5 Productivity and Processing Intensity

Dep. Var. TFP(OP)	(1)	(2)	(3)	(4)
Share of processing exports	-0.049***	-0.107***		
	(0.017)	(0.016)		
Share of processing products			-0.413***	-0.416***
			(0.028)	(0.027)
Size and FIE dummy	No	Yes	No	Yes
Observations	52,514	52,514	52,514	52,514
R-squared	0.324	0.367	0.329	0.372

Note: The sample is firms engaged in both processing and non-processing. Share of processing exports = (value of processing exports/total value of exports). Share of processing products = (# products exported through processing/# of all exported products). A product is defined to be exported through processing if more than half of its export value belongs to processing. All regressions include 4-digit Chinese industry, province, and year dummies. Columns (2) and (4) further include log employment and the foreign-invested-enterprise dummy. Standard errors are clustered at the firm level. *$p < 0.1$, **$p < 0.05$, ***$p < 0.01$.

Table 6: Productivity of Exporters by Processing, Ownership and Capital Intensity

Category	Ownership		Sectoral Capital Intensity		
	(1)	(2)	(3)	(4)	(5)
Dep. Var.: TFP(OP)	FIE	Non-FIE	Labor int.	Medium	Capital int.
Non-processing	0.065***	0.142***	0.104***	0.095***	0.145***
	(0.009)	(0.006)	(0.008)	(0.008)	(0.012)
Processing	-0.261***	0.021	-0.277***	-0.241***	-0.079**
	(0.013)	(0.030)	(0.016)	(0.015)	(0.036)
Hybrid	0.004	0.280***	0.061***	0.104***	0.137***
	(0.010)	(0.013)	(0.011)	(0.011)	(0.020)
Observations	164,617	637,212	223,997	361,288	216,544
R-squared	0.307	0.321	0.167	0.359	0.328

Note: This table reports the regression results of Equation 1. Columns (1) and (2) report results for FIE and non-FIE; Columns (3)-(5) report results for labor-intensive, medium, and capital-intensive sectors. Labor-intensive, medium, and capital-intensive sectors are defined based on the 33% and 67% quantile of sectoral capital-labor ratio. The dependent variable is TFP (Olley-Pakes). The omitted group is non-exporters. All regressions include firm-level log employment and the 4-digit Chinese industry, province, and year dummies. Columns (3)-(5) also include a FIE dummy. Standard errors are clustered at the firm level. *$p < 0.1$, **$p < 0.05$, ***$p < 0.01$.

Table 7: Other Performance of Processing Exporters

	(1)	(2)	(3)	(4)	(5)	(6)
Dep. Var. :	Log(K/L)	Log wages	Log sales	Profitability	Log R&D	Skill intensity
Non-processing	0.177***	0.108***	0.215***	3.040***	0.335***	0.028***
	(0.007)	(0.003)	(0.005)	(0.602)	(0.010)	(0.001)
Processing	0.021	-0.023***	-0.136***	-7.658***	-0.241***	-0.060***
	(0.015)	(0.006)	(0.012)	(1.094)	(0.013)	(0.002)
Hybrid	0.262***	0.157***	0.245***	1.501*	0.179***	-0.001
	(0.010)	(0.004)	(0.008)	(0.790)	(0.014)	(0.002)
Observations	801,829	801,827	801,829	801,829	801,829	156,347
R-squared	0.173	0.327	0.521	0.034	0.141	0.261

Note: This table reports the regression results of Equation 1. The dependent variables in columns (1)-(6) are the following: log capital-labor ratio, log average wage, log total sales, profit per worker, log R&D expenditure, and the share of skilled workers (workers with at least college education) over the total number of workers. The omitted group is non-exporters. All regressions include firm-level log employment, FIE dummy, and 4-digit Chinese industry, province, and year dummies. Standard errors are clustered at the firm level. *p $<$ 0.1, **p $<$ 0.05, ***p $<$ 0.01.

Table 8: Productivity of Processing Exporters across Sectors

	Advertisement Intensity		Sales Intensity		R&D Intensity	
	(1)	(2)	(3)	(4)	(5)	(6)
Dep. Var.: TFP(OP)	Low	High	Low	High	Low	High
Processing	-0.245***	-0.324***	-0.261***	-0.349***	-0.259***	-0.313***
	(0.016)	(0.018)	(0.013)	(0.027)	(0.014)	(0.021)
Hybrid	0.012	-0.028**	-0.001	-0.014	-0.010	0.005
	(0.010)	(0.012)	(0.009)	(0.016)	(0.009)	(0.014)
Observations	86,049	76,743	115,632	47,160	101,688	61,104
R-squared	0.300	0.338	0.308	0.374	0.317	0.356

Note: The dependent variable is TFP (Olley-Pakes). The omitted group is non-processing exporters. Columns (1)-(6) report results for industries with high (low) sales intensity, advertisement intensity, and R&D intensity. High/low sales (advertisement, R&D) intensity industries are defined based on the median sectoral ratio of selling expenses to total sales (ratio of advertising expenses to total sales, ratio of R&D expenses to total sales). All regressions include firm-level log employment, FIE dummy, and 4-digit Chinese industry, province, and year dummies. Standard errors are clustered at the firm level. *$p < 0.1$, **$p < 0.05$, ***$p < 0.01$.

Table 9: Productivity of Exporters by Detailed Processing Regime

	(1)	(2)	(3)
Dep. Var.:	TFP(OP)	TFP(ACF)	TFP(OLS)
Pure assembly	-0.435***	-0.426***	-0.350***
	(0.083)	(0.055)	(0.066)
Processing w/ imported inputs	-0.326***	-0.296***	-0.245***
	(0.081)	(0.051)	(0.062)
Hybrid	-0.075	-0.057	0.003
	(0.080)	(0.050)	(0.061)
Observations	162,792	162,792	162,792
R-squared	0.330	0.509	0.331

Note: The dependent variables in columns (1)-(3) are the following: TFP (Olley-Pakes), TFP (Ackerberg, Caves, Frazer), TFP (OLS). The omitted group is non-processing exporters. All regressions include firm-level log employment, FIE dummy, as well as 4-digit Chinese industry, province, and year dummies. Standard errors are clustered at the firm level. *$p < 0.1$, **$p < 0.05$, ***$p < 0.01$.

Table 10: The Role of Input tariffs Exemptions

Dep. Var.: TFP(OP)	(1) Low input tariffs ind.	(2) High input tariffs ind.	(3) Low input tariffs ind.	(4) High input tariffs ind.	(5) All firms
Processing	-0.249***	-0.302***			-0.070*
	(0.013)	(0.010)			(0.040)
Hybrid	0.011	-0.017**			0.154***
	(0.009)	(0.007)			(0.030)
Processing×log(tariffs)					-0.096***
					(0.018)
Hybrid×log(tariffs)					-0.073***
					(0.013)
Processing share			-0.109***	-0.206***	
			(0.011)	(0.008)	
Observations	62,155	100,637	62,155	100,637	162,792
R-squared	0.337	0.327	0.334	0.325	0.330

Note: Columns (1)-(2) regress TFP on a processing exporter dummy and a both dummy, respectively, in low input tariffs industries and high input tariffs industries. The omitted group is non-processing exporters. Columns (3)-(4) regress TFP on the share of processing exports in firms' total exports. Low and high input tariffs industries are classified according to the median of the input tariff levels at the 4-digit CIC level. All regressions include firm-level log employment, FIE dummy, as well as 4-digit Chinese industry, province, and year dummies. Standard errors are clustered at the firm level. *p $<$ 0.1, **p $<$ 0.05, ***p $<$ 0.01.

Table 11: The Role of Income Tax Benefits Granted to Export-oriented Firms

Dep. Var. : TFP(OP)	(1)	(2)	(3)
Eligible (expint>0.7)	-0.115***	-0.176***	
	(0.008)	(0.007)	
Non-processing		0.158***	
		(0.006)	
Processing		-0.150***	
		(0.011)	
Hybrid		0.162***	
		(0.008)	
Non-processing + Not Eligible			0.134***
			(0.006)
Non-processing + Eligible			0.033***
			(0.007)
Processing + Not Eligible			-0.056***
			(0.016)
Processing + Eligible			-0.363***
			(0.012)
Hybrid + Not Eligible			0.195***
			(0.010)
Hybrid + Eligible			-0.039***
			(0.009)
Observations	137,126	801,829	801,829
R-squared	0.342	0.315	0.315

Note: Column (1) regresses TFP on an eligible dummy. Eligible = 1 if the firm has export intensity above 0.7. Column (2) regresses TFP on processing status, adding the eligible dummy as an additional regressor. Column (3) regresses TFP on group dummies defined by firms' "processing status + eligible status". The omitted group in all columns is non-exporters. All regressions include firm-level log employment, FIE dummy, as well as 4-digit Chinese industry, province, and year dummies. Standard errors are clustered at the firm level. *p < 0.1, **p < 0.05, ***p < 0.01.

Table 12: Export Prices of Processing and Non-Processing Transactions

	Full Customs Data		Merged Data	
	(1)	(2)	(3)	(4)
Dep. Var. :$log(UV)_{ipcht}$	Export price	Import price	Export price	Import price
Processing	-0.032***	-0.862***	-0.066***	-0.837***
	(0.003)	(0.006)	(0.003)	(0.008)
FIE	0.406***	0.310***	0.089***	0.116***
	(0.003)	(0.002)	(0.002)	(0.005)
Product-country-year FE	Yes	Yes	Yes	Yes
Observations	25,031,434	15,671,611	5,268,129	6,362,401
R-squared	0.711	0.760	0.740	0.768

Note: This table reports regression results of Equation 2. The dependent variable is log export or import unit-value for a firm-hs6-country-processing-year pair. The omitted group is non-processing transactions. Columns (1) and (2) use the full customs data, while columns (3) and (4) use the merged data. All regressions include product-country-year fixed effects and an FIE dummy. Standard errors are clustered at the product-country-year level. *p < 0.1, **p < 0.05, ***p < 0.01.

Table 13 Other Policies

	Export License				Exchange Rate Reform	
	(1)	(2)	(3)	(4)	(5)	(6)
Dep. Var.: TFP(OP)	Before reform	After reform	Restricted ind.	Unrestricted ind.	Before reform	After reform
Non-processing	0.117***	0.105***	0.170***	0.103***	0.110***	0.112***
	(0.006)	(0.006)	(0.017)	(0.005)	(0.006)	(0.007)
Processing	-0.271***	-0.268***	-0.180***	-0.263***	-0.277***	-0.231***
	(0.012)	(0.014)	(0.053)	(0.011)	(0.011)	(0.016)
Hybrid	0.074***	0.072***	0.169***	0.070***	0.070***	0.085***
	(0.009)	(0.009)	(0.030)	(0.008)	(0.008)	(0.010)
Observations	518,053	283,776	59,896	741,933	638,971	162,858
R-squared	0.292	0.323	0.196	0.322	0.304	0.326

Note: The dependent variable is TFP (Olley-Pakes). The omitted group is non-exporters. Columns (1)-(4) examine the role of the export license system. Columns (1) and (2), respectively, report the results before the export license system was abolished (2000-2004) and after the system was abolished (2005-2006). Columns (3) and (4), respectively, report the results for industries that are restricted by export license and those that are not restricted. Columns (5)-(6) examine the role of China's exchange rate reform. Column (5) reports the results before the reform (2000-2005) and column (6) after the reform (2006). All regressions include firm-level log employment, FIE dummy, and 4-digit Chinese industry, province, and year dummies. Standard errors are clustered at the firm level. *p < 0.1, **p < 0.05, ***p < 0.01.

Table 14a: Transition Matrix of Processing Status, 1 Year Interval

	$Nonprocessing_{t+1}$	$Processing_{t+1}$	$Hybrid_{t+1}$
$Nonprocessing_t$	0.94	0.00	0.06
$Processing_t$	0.01	0.83	0.16
$Hybrid_t$	0.12	0.06	0.82

Table 14b: Transition Matrix of Processing Status, 6 Year Interval

	$Nonprocessing_{t+6}$	$Processing_{t+6}$	$Hybrid_{t+6}$
$Nonprocessing_t$	0.85	0.00	0.15
$Processing_t$	0.07	0.64	0.29
$Hybrid_t$	0.30	0.07	0.63

Note: Each number in the table is the probability of the firm's processing status in t + k, conditional on the processing status in t. Table 14a reports the results for k = 1 and 14b for k = 6.

7 Appendix (online only)

7.1 Appendix A: Matching Production and Trade Data Sets

Our discussion on matching the two data sets (i.e., firm-level production data and firm-customs data) here draws heavily from Yu (2015). We go through two steps to merge transaction-level trade data with firm-level production data. In the first step, we match the two data sets by firm name and year. The year variable is a necessary auxiliary identifier, since some firms could have different names across years and newcomers could possibly take their original names.

In the second step, we use another matching technique as a supplement. In particular, we adopt two other common variables to identify firms: zip code and the last seven digits of a firm's phone number. The rationale is that firms should have different and unique phone numbers within a postal district. Although this method seems straightforward, subtle technical and practical difficulties still exist. For instance, the production-level trade data set includes both area codes and a hyphen in the phone numbers, whereas the firm-level production data set does not. Therefore, we use the last seven digits of the phone number to serve as the proxy for firm identification for two reasons. First, during the period of 2000-2006, some large Chinese cities (e.g., Shantou in Guangdong province) added one more digit at the start of their seven-digit phone numbers. Therefore, sticking to the last seven digits of the number will not confuse firm identification. Second, in the original data set, phone numbers are defined as a string of characters with the phone zip code; however, it is inappropriate to de-string such characters to numerals because a hyphen is used to connect the zip code and phone number. Using the last seven-digit sub-string neatly solves this problem.

A firm might not include its name information in either the trade or the production data set. Similarly, a firm could lose its phone and/or zip code information. To be sure that our merged data set can cover as many common firms as possible, we then include observations in the matched data set if a firm occurs in either the name-adopted matched data set or the phone-and-post-adopted matched data set.

The merge results are shown in Appendix Table A2. Columns (1)-(2), (3)-(4), and (5)-(6) report the number of exporters and total export value in the ASIF production data, customs trade data, and the merged data by year, respectively. It is seen that the number of merged firms increased from 14,140 in the first sampled year to 39,399 in the last year, and total export value increased from 780 billion yuan to 3,512 billion yuan. Combining all years together, there are 68,865 exporters that are merged. These firms account for 58% of total export value in the firm-level production data, and 25% of China's total exports during 2000-2006.[23]

7.2 Appendix B: Construction of TFP (Olley-Pakes)

Here we describe in details the Olley-Pakes approach to estimating firms' TFP with some extensions. First, we adopt different price deflators for inputs and outputs. Data on input deflators and output deflators are from Brandt et al.(2012) in which the output deflators are constructed using reference price information from China's Statistical Yearbooks whereas input deflators are constructed based on output deflators and China's national input-output table in 2002.

Next, we construct the real capital stock of each firm-year pair using the perpetual inventory method proposed by Brandt et al.(2012). Rather than assigning an arbitrary number for the depreciation ratio, we use the firm's real depreciation rate provided by the Chinese firm-level data set. Real investment is constructed as the first difference of the nominal value of fixed capital at the original purchase prices, and then deflated by the Brandt-Rawski investment deflator, as in Brandt et al.(2012). Labor input is measured by the total number of workers.

We then work with a standard log specification of the Cobb-Douglas production function:

$$y_{it} = \beta_l l_{it}. + \beta_k k_{it} + \beta_m m_{it} + \omega_{it} + \varepsilon_{it} \tag{1}$$

[23] By way of comparison, our matching performance is highly comparable with that of other similar studies, such as Ge et al. (2015).

where y_{it} is the gross output of firm i in year t, and l_{it}, k_{it},and m_{it} denote labor, capital, and intermediate inputs respectively, all in logs. By assuming that the expectation of future realization of the unobserved productivity shock relies on its contemporaneous value ω_{it}, firm i's log investment (inv_{it}) is modeled as an increasing function of both unobserved productivity and log capital. Following previous works, such as Van Biesebroeck (2005) and Amiti and Konings (2007), we also add the firm's export status as an extra argument of the investment function:

$$inv_{it} = \tilde{I}(k_{it}, \omega_{it}, FX_{it}) \tag{2}$$

where FX_{it} is a dummy to measure whether firm i exports in year t. Inverting inv_{it} we can express the unobserved productivity as a function of capital and export status:

$$\omega_{it} = \tilde{I}^{-1}(k_{it}, inv_{it}, FX_{it}) \tag{3}$$

Accordingly, the estimation specification can now be written as:

$$y_{it} = \beta_0 + \beta_l l_{it} + \beta_m m_{it} + g(k_{it}, inv_{it}, FX_{it}) + \varepsilon_{it} \tag{4}$$

Where $g(k_{it}, inv_{it}, FX_{it})$ is defined as $\beta_k k_{it} + \tilde{I}^{-1}(k_{it}, inv_{it}, FX_{it})$. Following Olley and Pakes (1996) and Amiti and Konings (2007), fourth-order polynomials are used in log-capital, log-investment and firm's export dummy to approximate $g(.)$. In addition, as in Feenstra et al.(2014), we also include a WTO dummy (i.e., 1 for a year after 2001 and 0 for before) to characterize the function $g(.)$as follows:

$$g(k_{it}, inv_{it}, FX_{it}, WTO_t) = (\alpha_0 + \alpha_1 WTO_t + \alpha_2 FX_{it}) \sum_{h=0}^{4} \sum_{q=0}^{4} \delta_{hq} (k_{it})^h inv_{it}^q. \tag{5}$$

After finding the estimated coefficients $\widehat{\beta}_m$ and $\widehat{\beta}_l$, we calculate the residual which is defined as $R_{it} \equiv y_{it} - \hat{\beta}_m m_{it} - \hat{\beta}_l l_{it}$.

The next step is to obtain an unbiased estimated coefficient of β_k. We assume firm's productivity follows a Markov process, $\omega_{it} = h(\omega_{i,t-1}, FX_{i,t-1}) + \epsilon_{it}$. As in De Loecker(2007), we assume that current productivity is affected by the firm's export status in the previous period. This captures the possible "learning by exporting" effect. To correct the selection bias due to firm exit, we follow Amiti and Konings (2007) and enter the probability of a survival indicator on a high-order polynomial in log-capital and log-investment. One can then accurately estimate the following specification:

$$R_{it} = \beta_k k_{it} + \tilde{I}^{-1}(g_{i,t-1} - \beta_k k_{i,t-1}, \hat{pr}_{i,t-1}, FX_{i,t-1}) + \epsilon^*_{it}, \tag{6}$$

where $\hat{pr}_i$ denotes the fitted value for the probability of the firm 's exit in the next year and $\epsilon^*_{it} = \epsilon_{it} + \varepsilon_{it}$ is a composite error. Since the specific "true" functional form of the inverse function $\tilde{I}^{-1}(\cdot)$ is unknown, it is appropriate to use fourth-order polynomials in $g_{i,t-1}$ and $k_{i,t-1}$ to approximate it. In addition, (6) also requires the estimated coefficients of the log-capital in the first and second terms to be identical. Therefore, non-linear least squares is used (Pavcnik, 2002). Finally, the Olley–Pakes type of TFP for ordinary firm i in industry j is obtained once the estimated coefficient $\hat{\beta}_k$ is obtained:

$$\ln TFP_{ijt}^{OP} = y_{it} - \hat{\beta}_m m_{it} - \hat{\beta}_k k_{it} - \hat{\beta}_l l_{it}. \tag{7}$$

In our implementation, we estimate the production function separately for each 2-digit CIC industry, thus allowing technology to vary industry-by-industry.

7.3 Appendix C: A Theoretical Structure for Modeling Processing versus Non-Processing Exporters

In this appendix we sketch a theoretical model for explaining the productivity patterns of the different types of exporters observed in the data.[24] We consider an augmented Melitz (2003) model with two countries and one sector producing differentiated goods.

Consumer utility takes the standard CES form over varieties, with σ describing the elasticity of substitution across varieties. Firms in the differentiated good sector uses labor for production, with increasing returns to scale technology. For simplicity, we normalize the wage rate to 1. Firms are heterogeneous in productivity φ which is drawn from a common distribution after a sunk entry cost is paid. The market structure is monopolistic competition.

To focus on the rationales behind the choice between processing and non-processing trade, for now we assume that firms can only export. We relax this assumption and allow for domestic sales in the extension. A firm can choose to export through one of the two trade regimes: processing (PR) and non-processing (NPR).[25] Both the variable and the fixed cost of exporting depend on the exporting regime. The variable and fixed cost associated with processing export is described by τ_{PR} and f_{PR}, while those for non-processing trade are τ_{NPR} and f_{NPR}. We assume that firms can choose to export a certain product through one of the two regimes (e.g. if doing both activities incurs prohibitive transition cost).

We make several assumptions to highlight the special features of processing trade. (i) We assume that the variable cost of processing is lower than that of non-processing export (i.e. $\tau_{NPR} > \tau_{PR}$) due to the tariffs exemption granted to processing activities. (ii) We assume that the fixed cost of processing export is lower than that of non-processing exports (i.e. $f_{NPR} > f_{PR}$). As described in the main text, there are several reasons why the fixed cost of exporting might be low. First, in a processing trade relationship, the foreign buyer is responsible for marketing and distribution of the final product, thus reducing the distribution cost born by the local processing manufacturer. Second, for the processed final product to meet certain quality requirements, the foreign buyer usually provides the know-hows and blueprint for the final product, and also the key parts and components that embed sophisticated technology. Therefore, the research and development costs on the processing firm side can be substantially lowered. (iii) We assume that processing exports are conducted only after receiving foreign contracts. Since the contract is incomplete, the processing exporter and foreign buyer are involved in ex-post bargaining over the distribution of total variable profit. For simplicity, we assume that the processing exporter get a share $\phi_{PR} < 1$ of the total profit. Therefore, processing exports are associated with profit sharing which leads to a lower variable profit rate compared with non-processing exports.

These assumptions generate the main trade-off between processing and non-processing exports. By engaging in processing trade, a firm gains from the lower fixed cost of exporting (and also lower variable trade cost due to import tariffs exemptions) but loses from the reduction in the variable profit rate. Since the lower profit rate translates into more profit loses for more productive firms, firms with high productivity will optimally choose to export through non-processing, whereas firms with low productivity will optimally export through processing.

Formally, we can write the profit for each exporting mode as a function of firm productivity, φ.

$$\begin{cases} \pi_{PR} = \phi_{PR}\tau_{PR}^{1-\sigma}\varphi^{\sigma-1}A - f_{PR} \\ \\ \pi_{NPR} = \tau_{NPR}^{1-\sigma}\varphi^{\sigma-1}A - f_{NPR} \end{cases} \tag{1}$$

[24] Manova and Yu (2013) have also developed a model incorporating processing and ordinary trade. They focus on liquidity constraints and show that firms that are less liquidity constrained select into processing trade.

[25] Here we do not consider the case of engaging in both processing and non-processing. Although 23 percent of the firms in our data set are engaged in both processing and non-processing, it is mainly because firms export some products through processing and others through non-processing. At the firm-product level, 97 percent of the firm-product pairs are exported through a single trade mode. Our model describes the firms' choice between processing and non-processing in exporting a single product.

where A summarizes the aggregate variables that the firm takes as exogenous (such as aggregate income and price index).

Firms choose the exporting mode that maximizes profits. As a result, firms with different productivity will sort into different exporting modes.

7.3.1 Exit v.s. Processing

Firms choose to engage in processing exports over exit when $\pi_{PR} > 0$. Plugging in the expression of π_{PR} and setting profit to zero, we can obtain the cut-off point where firms are indifferent between processing exports and exit.

$$\varphi^*_{PR} = \left(\frac{f_{PR}}{\phi_{PR}\tau_{PR}^{1-\sigma}A}\right)\frac{1}{\sigma-1} \tag{2}$$

Firms with $\varphi > \varphi^*_{PR}$ will choose processing exports, while firms with $\varphi < \varphi^*_{PR}$ choose to exit.

7.3.2 Processing v.s. Non-Processing

By the same token, we compare the profit function for processing and non-processing exports. It is easy to show that under the following condition:

$$\phi_{PR} < \left(\frac{\tau_{NPR}}{\tau_{PR}}\right)^{1-\sigma} \tag{3}$$

That is, when the disadvantage of the lower profit rate for processing exports is large enough to offset its advantage of relatively lower variable trade cost, there exists an cut-off productivity φ^*_{NPR}, such that firms with $\varphi > \varphi^*_{NPR}$ will choose to engage in non-processing exports, and firms with $\varphi \in (\varphi^*_{PR}, \varphi^*_{NPR})$ will choose processing exports. The cut-off productivity is given by

$$\varphi^*_{NPR} = \left[\frac{f_{PR} - f_{NPR}}{(\phi_{PR}\tau_{PR}^{1-\sigma} - \tau_{NPR}^{1-\sigma})A}\right]^{\frac{1}{\sigma-1}} \tag{4}$$

To replicate the sorting pattern in our data, we need to ensure the cut-off productivity for non-processing-processing is higher than the cut-off productivity for processing-exit. Letting $\varphi^*_{NPR} > \varphi^*_{PR}$, we obtain the following condition:

$$\frac{\boldsymbol{\tau}_{NPR}^{1-\sigma}}{\boldsymbol{\phi}_{PR}\boldsymbol{\tau}_{PR}^{1-\sigma}} < \frac{f_{NPR}}{f_{PR}} \tag{5}$$

Proposition 1 *Under assumptions (i)-(iii) and conditions (3) and (5), there exist cut-off points φ^*_{PR} and φ^*_{NPR} such that firms with productivity lower than φ^*_{PR} exit, firms in the productivity range $(\varphi^*_{PR}, \varphi^*_{NPR})$ engage in processing exports, and firms with productivity higher than φ^*_{NPR} engange in non-processing exports.*

Although we assume that a firm can choose only one trade regime to export a certain product, mixed strategies at the firm level can exist if a firm exports multiple products and different product lines are associated with different productivity. In such cases, firms will optimally choose processing for the product lines with lower productivity, and non-processing for those with higher productivity. Aggregating at the firm level, this suggests that firm-level productivity will be decreasing in firms' processing intensity (processing exports/total exports). This is supported by the estimation results in Table 5, in which firms with higher processing intensity have lower productivity.

To derive further testable predictions from the model, first note that the average productivity of each type of exporters can be written as a function of the productivity cut-off corresponding to that export mode. Denoting the average productivity of exporters enaged in processing and non-processing as $\widetilde{\varphi}_{PR}$ and $\widetilde{\varphi}_{NPR}$, we have $\widetilde{\varphi}_{PR} = \widetilde{\varphi}_{PR}(\varphi^*_{PR})$ and $\widetilde{\varphi}_{NPR} = \widetilde{\varphi}_{NPR}(\varphi^*_{NPR})$. It can be established that the relative average productivity of the two types of exporters will be a function of the relative productivity cut-offs, $\frac{\widetilde{\varphi}_{PR}}{\widetilde{\varphi}_{NPR}} = \widetilde{\varphi}(\frac{\varphi^*_{PR}}{\varphi^*_{NPR}})$,with $\widetilde{\varphi}'(.) > 0$. Substituting φ^*_{PR} and φ^*_{NPR} with their expressions in (2) and (4), we get

$$\frac{\widetilde{\varphi}_{PR}}{\widetilde{\varphi}_{NPR}} = \widetilde{\varphi}\{[\frac{1}{\phi_{PR}}(\frac{\tau_{PR}}{\tau_{NPR}})^{\sigma-1} - 1](\frac{1}{1-\frac{f_{NPR}}{f_{PR}}})\} \tag{6}$$

where $\frac{1}{\phi_{PR}}(\frac{\tau_{PR}}{\tau_{NPR}})^{\sigma-1} > 1$ according to (3). From Equation (6), the productivity of processing exporters relative to non-exporters depends on both the relative variable trade costs of processing exports (which in our context captures the tariffs exemptions granted to exporters), as well as the relative fixed costs of processing exports.

7.3.3 Fixed Costs of Exporting and Relative Productivity of Processing Exporters

It is easy to see from Equation (6) that $\frac{\widetilde{\varphi}_{PR}}{\widetilde{\varphi}_{NPR}}$is decreasing in $\frac{f_{NPR}}{f_{PR}}$. That is, processing exporters will on average exhibit lower relative productivity to non-processing exporters if engaging in processing is associated with larger (in proportional terms) savings of fixed costs.

In principle, we can test this prediction by constructing a measure of the relative fixed costs $\frac{f_{NPR}}{f_{PR}}$ by averaging the fixed cost variables (i.e. advertising intensity or R&D intensity)of non-processing exporters over processing exporters within each sector. However, in practice such measures may suffer from a serious endogeneity problem because we are constructing these measures using indicators that might be highly correlated with relative productivity. For example, if more productive firms also invest more in advertisement and R&D, there will exist a mechanical positive correlation between relative productivity and the constructed relative fixed cost measures.

To circumvent this issue, we need to put more structure on the relative fixed costs. In particular, we make the assumption that $\frac{f_{NPR}}{f_{PR}}$ in a sector is increasing in the fixed cost requirement of that sector. That is, $\frac{\partial(f_{NPR}/f_{PR})}{\partial \overline{f}} > 0$, where $\overline{f}$ is the average fixed cost of exporting in the sector. This assumption makes intuitive sense: in a sector where exporting requires substantial investment in distribution, marketing and research and development, the fixed cost reduction by engaging in processing trade is likely to be larger, since engaging in processing trade waives all the responsibilities of the processing firm in making these investments.

With this assumption, we have the following proposition:

Proposition 2 *The average productivity of processing exporters relative to non-processing exporters,* $\frac{\widetilde{\varphi}_{PR}}{\widetilde{\varphi}_{NPR}}$ *, is decreasing in the in the average fixed cost of exporting in a sector,* $\overline{f}$.

7.3.4 tariffs Exemptions and Relative Productivity of Processing Exporters

Equation (6) also reveals the impact of tariffs exemptions granted to processing exporters. From (6), $\frac{\partial(\widetilde{\varphi}_{PR}/\widetilde{\varphi}_{NPR})}{\partial(\tau_{PR}/\tau_{NPR})} > 0$. That is, the relative productivity of processing exporters will be lower if processing trade is associated with lower relatively variable trade costs. Relating this to input tariffs exemptions, since processing exports are duty-free, an increase in the tariffs rates for non-processing exporters leads to a decrease in (τ_{PR}/τ_{NPR}). Thus, we have the following proposition:

Proposition 3 *The productivity of processing exporters relative to non-processing exporters is lower in sectors with higher input tariffs.*

7.3.5 Extension: Allowing for Domestic Sales

The model can be extended to include domestic sales. Now suppose that a firm can either sell a product domestically, or export it through processing or non-processing. For domestic sales, we assume that the domestic trade costs τ_D=1. The firm also incurs a fixed sales cost f_D. In addition, like non-processing trade, we assume there are no profit sharing issues for domestic sales, so $\boldsymbol{\phi}_D$=1.

Under these assumptions, the profit function for domestic sales can be written as

$$\pi_D = \varphi^{\sigma-1}A - f_D \tag{2}$$

The profit function for processing and non-processing exports are still described by Equation (1).

Our baseline regression results suggest that processing exporters are less productive than non-exporters. To replicate this pattern, we make the following assumptions: (1) $\phi_{PR}\tau_{PR}^{1-\sigma} < 1$. (2) $f_{PR} < f_D$.

The first assumption is a natural one because $\phi_{PR} < 1$ and τ_{PR} is usually greater than 1 (unless the tariffs and tax benefits granted to processing exporters are sufficiently large). What needs explanation is the second one. In the literature, it is usually assumed that the fixed costs of exporting are higher than that of domestic sales. However, there are several reasons we believe that it is possible for the fixed costs of *processing* exports to be lower than that of domestic sales. The first reason is that processing exporters are not responsible for the activities that are usually thought to constitute the major components of the fixed costs of exporting, such as design, distribution and marketing of the final product, while domestic sales do require these activities. The second reason is related to the special context of China. It has been widely documented that engaging in domestic sales in China is difficult. The reasons include corruption (Cai et al. 2011), local protectionism (Bai et al. 2004; Poncet 2005), and lack of creditability between sellers and buyers, which often leads to payment delay or default.

With these assumptions, the sorting among domestic sales, processing exports, and non-processing exports can be summarized as follows:

Proposition 4 *There exist cut-off points φ^*_{PR} , φ^*_D and φ^*_{NPR} such that firms with productivity lower than φ^*_{PR} exit, firms in the productivity range $(\varphi^*_{PR}, \varphi^*_D)$ engage in processing exports, firms in the productivity range $(\varphi^*_D, \varphi^*_{NPR})$ engage in domestic sales. and firms with productivity higher than φ^*_{NPR} engage in non-processing exports.*

Table A1: Export intensity by processing status

Processing Status	(1) Export intensity	(2) Exp. intensity >0.7	(3) Exp. intensity >0.9	(4) Exp. intensity =1
Non-processing	0.40	0.32	0.23	0.14
Processing	0.76	0.71	0.63	0.51
Hybrid	0.64	0.56	0.43	0.26

Note: Export intensity=export/sales. All statistics are calculated using the merged data. Column (1) reports export intensity. Columns (2)-(4) report the share of firms with export intensity above a certain threshold.

Table A2: Merging results

Year	Production data		Trade data		Merged data	
	#exporter	Export value (bil. yuan)	#exporter	Export value (bil. yuan)	#exporter	Export value (bil. yuan)
2000	36,598	1,414	62,746	2,492	14,140	780
2001	40,247	1,583	68,487	2,660	16,488	903
2002	44,754	1,960	78,612	3,256	19,301	1,141
2003	50,414	2,640	95,688	4,382	23,289	1,547
2004	76,310	3,993	120,590	5,933	37,999	2,381
2005	74,286	4,706	144,030	7,567	35,959	2,699
2006	77,898	5,975	171,205	9,685	39,399	3,512

Table A3: Replications of counter-Melitz findings

Category	Ownership		Sectoral Capital Intensity		
	(1)	(2)	(3)	(4)	(5)
	FIE	non-FIE	Labor intensive	Medium	Capital intensive
Exporter dummy	-0.043***	0.154***	-0.058***	0.014*	0.186***
	(0.008)	(0.006)	(0.008)	(0.008)	(0.013)
Observations	164,617	637,212	223,368	359,873	215,915
R-squared	0.301	0.321	0.159	0.170	0.204

Note: This table reports regressions of the dependent variable on the exporter dummy. The omitted group is non-exporters. Columns (1) and (2) report results for FIE and non-FIE; columns (3)-(5) report results for labor-intensive, medium, and capital-intensive sectors. Labor-intensive, medium, and capital-intensive sectors are defined based on the 33% and 67% quantile of sectoral capital-labor ratio. The dependent variables in columns (1) and (2) are TFP (Olley-Pakes), and in columns (3) and (4) labor productivity. All regressions include 4-digit Chinese industry, province, and year fixed effects and log employment. Standard errors are clustered at the firm level. *$p < 0.1$, **$p < 0.05$, ***$p < 0.01$.

Table A4 Share of observations by processing status at different levels of aggregation

	(1)	(2)	(3)
Level of aggregation	Firm-year	Firm-product-year	Firm-product-country-year
Non-processing	0.63	0.89	0.86
Processing	0.14	0.08	0.11
Hybrid	0.23	0.03	0.03

Note: This table reports the share of observations in the customs data at various aggregation levels. An observation in Columns (1)-(3) is respectively a firm-year pair, firm-HS6-year pair, and firm-HS6-country-year pair.

Table A5: Production Coefficients by Processing and Non-Processing Firms Separately

Chinese	Non-Processing Firms			Processing Firms		
Industry	Labour	Materials	Capital	Labour	Materials	Capital
13	0.242	0.875	0.052	0.116	0.884	0.066
14	0.023	0.926	0.050	0.037	0.925	0.074
15	0.185	0.508	0.268	0.243	0.505	0.088
17	0.017	0.884	0.059	0.089	0.834	0.041
18	0.054	0.858	0.076	0.177	0.669	0.142
19	0.126	0.895	0.023	0.118	0.808	0.000
20	0.126	0.895	0.023	0.044	0.913	0.003
21	0.055	0.917	0.042	0.101	0.873	0.103
22	0.111	0.907	0.008	0.027	0.896	0.063
23	0.023	0.821	0.039	0.105	0.836	0.025
24	0.068	0.764	0.123	0.104	0.863	0.036
26	0.086	0.795	0.063	0.007	0.927	0.024
27	0.108	0.862	0.040	0.038	0.860	0.038
28	0.116	0.789	0.033	0.016	0.837	0.041
29	0.061	0.569	0.174	0.073	0.938	0.032
30	0.118	0.633	0.182	0.125	0.696	0.114
31	0.073	0.851	0.047	0.050	0.870	0.035
32	0.046	0.976	0.051	0.038	0.961	0.010
33	0.053	0.815	0.080	0.055	0.850	0.076
34	0.041	0.867	0.048	0.044	0.883	0.026
35	0.065	0.875	0.024	0.032	0.917	0.026
36	0.090	0.823	0.076	0.038	0.869	0.111
37	0.058	0.888	0.047	0.054	0.924	0.029
39	0.013	0.830	0.103	0.102	0.826	0.000
40	0.071	0.831	0.072	0.086	0.878	0.086
41	0.081	0.906	0.015	0.139	0.567	0.168
42	0.055	0.917	0.045	0.142	0.818	0.094

Notes: This table draws from Yu (2015). It reports the production coefficients estimated using the Olley-Pakes approach by separating ordinary firms and processing firms. The Chinese industries and associated codes are classified as follows: Processing of foods (13), Manufacture of foods (14), Beverages (15), Textiles (17), Apparel (18), Leather (19), Timber (20), Furniture (21), Paper (22), Printing(23), Articles for cultures and sports (24), Petroleum (25), Raw chemicals (26), Medicines (27), Chemical fibers (28), Rubber (29), Plastics (30), Non-metallic minerals (31), Smelting of ferrous metals (32), Smelting of non-ferrous metals (33), Metal (34), General machinery (35), Special machinery (36), Transport equipment (37), Electrical machinery (39), Communication equipment (40), Measuring instruments (41), and Manufacture of artwork (42).